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Modelling Annual Temperature Using Selected Climatic Variables in Nigeria: An All-Subsets Regression Approach

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Abstract

This study examined the relationship between temperature and selected climatic variables, humidity, rainfall, precipitation, and wind using multiple regression modeling to identify the most suitable predictive model for temperature variation. Fifteen possible regression models were estimated and evaluated using regression coefficients, analysis of variance (ANOVA), coefficient of determination (R^2), adjusted R^2, and mean square error (MSE). The results shows that model 10 (X_3X_4), comprising precipitation and wind, recorded a relatively high explanatory power with $R^2 = 0.406$ and adjusted $R^2 = 0.368$, indicating that approximately 40.6% of the variation in temperature is explained by the model. However, models 12 and 13 demonstrated even stronger performance, with R^2 values of 0.452 and 0.451 respectively, suggesting better predictive accuracy. Model 13 (Humidity, Precipitation, and Wind) recorded the highest adjusted R^2 of 0.396 and the lowest MSE of 0.054, indicating that it provides the best balance between explanatory power and prediction error, while humidity and rainfall showed weak individual predictive power. Out of the fifteen estimated models, twelve were statistically significant at the 5% level. Among the models, the combination of humidity, precipitation, and wind produced the best predictive performance with the highest adjusted R^2 and lowest mean square error, indicating superior explanatory ability. The findings further showed that precipitation had a negative relationship with temperature, while wind had a positive influence. This suggests that temperature variability is largely driven by the interaction of multiple climatic factors rather than isolated variables. The study concludes that multiple regression provides a reliable framework for understanding climatic relationships and can serve as a useful tool for climate prediction and environmental planning. The results provide empirical evidence for improved climate monitoring and policy formulation aimed at mitigating the effects of climate variability.

Keywords: Temperature, Climate variability, Multiple regression, Precipitation, Wind, Environmental modeling.

Introduction

Climate change has emerged as one of the most significant global environmental challenges of the twenty-first century, with profound implications for human livelihoods, ecological systems, and economic development. The phenomenon is associated with rising global temperatures, increasing frequency and intensity of extreme weather events, prolonged droughts, irregular rainfall patterns, sea-level rise, and biodiversity loss. According to the Intergovernmental Panel on Climate Change, climate change is already affecting every inhabited region of the world through intensified heatwaves, flooding, desertification, and disruptions to agricultural and water systems (IPCC, 2023). These impacts are expected to increase substantially over time, imposing significant social and economic costs, particularly in developing countries with limited adaptive capacity.

Although the terms *global warming* and *climate change* are often used interchangeably, they represent distinct but related concepts. Global warming specifically refers to the long-term increase in Earth's average surface temperature due to anthropogenic greenhouse gas emissions, while climate change encompasses broader long-term alterations in temperature, precipitation patterns, atmospheric circulation, and ecological systems (NASA, 2023). Scientific evidence indicates that changes in solar radiation, volcanic eruptions, ocean circulation, and anthropogenic activities collectively influence climatic variability, though recent accelerated warming is predominantly linked to human activities such as fossil fuel combustion and deforestation (WMO, 2025).

In Nigeria, climate variability has become increasingly evident across the country's diverse ecological zones, with significant consequences for environmental sustainability and socioeconomic development. Nigeria's tropical climate is characterized by two major precipitation regimes: low rainfall in the northern regions and relatively high rainfall in the southern coastal areas. These variations contribute to contrasting climate-related hazards such as desertification and drought in the north, and flooding, erosion, and coastal inundation in the south (NIMET, 2025).

Northern Nigeria, particularly the Sudan-Sahel ecological zone, remains highly vulnerable to climate change due to prolonged droughts, declining rainfall, and advancing desertification. Recent evidence shows that reduced precipitation and increasing temperatures have intensified water scarcity, caused drying of wetlands and reservoirs, reduced agricultural productivity, and exacerbated resource-based conflicts (Ayanlade et al., 2018; Ogbuabor & Egwuchukwu., 2017). The shrinking of Lake Chad remains one of the most visible indicators of climate stress in the region, affecting millions of people who depend on it for farming, fishing, and domestic water supply (UNEP, 2004).

Similarly, southern Nigeria faces increasing vulnerability to climate-induced flooding, coastal erosion, and sea-level rise. The Niger Delta region is particularly susceptible due to its low-lying topography and exposure to storm surges and tidal inundation. Recent flood events across states such as Lagos, Bayelsa, and Rivers have displaced thousands of residents, destroyed infrastructure, disrupted livelihoods, and heightened public health risks (World Bank Group, 2021). Seasonal flooding has become more intense due to increased rainfall variability and inadequate urban drainage systems.

Climate records indicate that Nigeria has experienced a significant increase in average annual temperature over the past four decades, with warming trends estimated at approximately 0.2–0.3°C per decade across ecological zones (NIMET, 2025). Rainfall patterns have also become increasingly erratic, characterized by delayed onset, early cessation, and uneven spatial distribution. Such variability has severe implications for rain-fed agriculture, which remains the primary source of livelihood for a

substantial proportion of the population.

The implications of climate change for Nigeria extend beyond environmental degradation to include threats to food security, public health, energy supply, water resources, and national security. Given Nigeria's heavy dependence on climate-sensitive sectors such as agriculture and fisheries, effective adaptation and mitigation strategies are essential for sustainable development. This necessitates continuous empirical studies aimed at understanding climate variability patterns and informing evidence-based policy responses.

The aim of this study is to know the effect of climate change using temperature, humidity rainfall, precipitation and wind. The objectives are to fit all possible two variables and three variable linear model to the data, to compute R-square adjusted, mean square error and test parameter significances for each fitted model and to select the best regression fitted model on the basis of R-square adjusted.

Statement of the Problem

Nigeria continues to experience severe climate-related challenges despite several policy interventions and international commitments aimed at climate adaptation and mitigation. Rising temperatures, erratic rainfall patterns, prolonged droughts, and recurrent flooding have increasingly threatened agricultural productivity, water availability, ecosystem stability, and human settlements. The northern region of Nigeria has experienced persistent drought conditions, desert encroachment, and declining water resources, resulting in shrinking agricultural output, displacement of rural populations, and intensified farmer-herder conflicts. These environmental stresses have contributed to social instability, food insecurity, and increased vulnerability among already marginalized populations. In particular, the continued shrinkage of Lake Chad has worsened livelihood insecurity and regional conflict dynamics. In southern Nigeria, recurrent flooding and coastal erosion have caused substantial economic losses, destruction of infrastructure, and displacement of communities. Major urban centers such as Lagos increasingly face annual flood disasters due to rising sea levels, intense rainfall events, and poor drainage infrastructure (World Meteorological Organization, 2025). Despite growing awareness of climate change, policy implementation in Nigeria remains constrained by inadequate funding, weak institutional coordination, insufficient climate data infrastructure, and limited integration of climate projections into national development planning. Furthermore, uncertainties surrounding future climatic conditions present challenges for long-term policy formulation and adaptation planning. There is therefore an urgent need for empirical studies that provide updated statistical evidence on climate variability trends in Nigeria. Such studies are essential for understanding the magnitude, spatial distribution, and temporal patterns of climate change impacts. Findings from this research will support the formulation of effective adaptation strategies, strengthen resilience planning, and contribute to sustainable national development.

Literature Review

Climate change has become one of the most extensively studied environmental issues due to its multidimensional implications for ecological sustainability, economic development, and human survival. It refers to long-term alterations in average weather patterns, including temperature, precipitation, humidity, and atmospheric circulation over extended periods, usually spanning decades or longer. According to the Intergovernmental Panel on Climate Change (2023), climate change is primarily driven by anthropogenic activities that alter the composition of the atmosphere through excessive greenhouse gas emissions.

The climate system is naturally dynamic and has undergone periodic changes throughout Earth's geological history. However, contemporary climate change differs from historical variability because of the unprecedented rate and magnitude of warming associated with industrialization, deforestation, urbanization, and unsustainable energy consumption (World Meteorological Organization, 2025). Scientific evidence indicates that the Earth's average surface temperature has increased by approximately 1.1°C above pre-industrial levels, with further warming projected if mitigation measures are not intensified.

The concept of climate change gained global policy significance following the establishment of the United Nations Framework Convention on Climate Change (UNFCCC) and subsequent international climate protocols. It is now recognized not only as an environmental issue but also as a developmental challenge with implications for agriculture, health, water resources, infrastructure, and social stability.

Causes and Effects of Climate Change

Climate change is primarily driven by both anthropogenic and natural factors, although contemporary scientific evidence shows that human activities are the dominant contributors. Anthropogenic causes include the burning of fossil fuels for industrial production, transportation, and electricity generation, which releases large amounts of carbon dioxide into the atmosphere. Other significant human-induced causes include deforestation, agricultural activities that emit methane and nitrous oxide, and industrial emissions that increase greenhouse gas concentrations. According to the Intergovernmental Panel on Climate Change (2023), atmospheric carbon dioxide concentrations have risen to over 420 parts per million, representing the highest levels recorded in over two million years. Natural causes such as variations in solar radiation, volcanic eruptions, ocean circulation patterns, and orbital changes also influence climatic variability, but recent warming trends are predominantly attributed to anthropogenic forcing (NASA, 2023).

The effects of climate change are extensive and multidimensional, affecting environmental systems, economic activities, and human well-being. Environmentally, climate change has led to rising global temperatures, increased frequency of extreme weather events, desertification, sea-level rise, and biodiversity loss. Socioeconomically, it threatens food security, public health, infrastructure, and economic productivity, with vulnerable populations experiencing disproportionate impacts due to limited adaptive capacity. The World Bank Group (2021) notes that climate change could reverse decades of development gains in low-income countries if urgent interventions are not implemented.

In Nigeria, climate change has significantly affected agriculture, water resources, public health, and social stability. Variability in rainfall, prolonged drought, and increasing temperatures have reduced agricultural productivity, particularly in the northern regions where farming depends heavily on rainfall (Ayanlade et al., 2018). Water scarcity resulting from the shrinking of Lake Chad and declining river flow has intensified resource competition, while southern Nigeria, especially the Niger Delta and Lagos, faces increased risks of flooding and coastal erosion. These challenges have contributed to migration, displacement, public health risks, and communal conflicts, highlighting the need for effective mitigation and adaptation strategies such as renewable energy adoption, afforestation, climate-smart agriculture, flood-control infrastructure, and early warning systems.

Empirical Review

Several recent empirical studies have examined the impacts of climate change in Nigeria across agriculture, water resources, hydrology, and economic development. Ayanlade et al., (2018) found that increased temperature variability and erratic rainfall have significantly reduced agricultural productivity

in Nigeria. In the Niger Delta, Agumagu and Todd (2015) identified increased flood risks due to projected river discharge increases, while Ogbuabor and Egwuchukwu (2017) established that carbon emissions and rainfall variability negatively affect Nigeria's economic growth.

Institutional reports also support these findings. The United Nations Environment Programme (2004) identified shrinking freshwater resources and desertification as critical climate risks in the Lake Chad Basin. Despite these contributions, important gaps remain in the literature. Most studies focus on isolated sectors such as agriculture, flooding, or water resources and often rely on outdated datasets that do not adequately capture recent climatic variability. Furthermore, there is limited integrated statistical evidence on long-term climate trends across Nigeria's ecological zones. This study addresses these gaps by providing an updated and comprehensive statistical analysis of climate variability and its implications for sustainable development in Nigeria.

Materials and Methods

In statistics, 'all possible regression procedure" is a statistical technique for estimating the relationship between the dependent variable and the independent variables. It includes many techniques for modelling and analysing variables, especially when the focus is on the relationship between the dependent variable and the independent variables. "ALL POSSIBLE REGRESSION" is a combination of the linear and multiple regressions. In this study, we have our variable" Y" TEMPERATURE and four (4) independent variables X_1,X_2,X_3 and X_4. The all-possible regression procedure fits all regressions involving one regressor, two regressors, three regressors, and so on. The selection criterion is recorded for each subset size is determined. Then determine which subset size is optimum for the case. Therefore, we will have 2^n - 1 ie 16-1= 15 possible regression models are YX_1, YX_2, YX_3, YX_4, YX_1X_2, YX_1X_3, YX_1X_4, YX_2X_3, YX_2X_4, $YX_1X_2X_3$, $YX_2X_3X_4$, $YX_1X_3X_4$, $YX_1X_2X_3$, $YX_1X_2X_3X_4$.

Where;

Y- TEMPERATURE

X_1- HUMIDITY

X_2- RAINFALL

X_3- PRECIPITATION

X_4- WIND

The method used for parameter estimation is: Y= $B0$, BX_1, BX_2, BX_3, BX_4

Source of Data

The data for this study was sourced from the data base of the National Bureau of Statistics from (1990 to 2023) representing the meteorological aggregate of Nigeria.

Multiple Linear Regressions

The multiple linear regressions is most common form of linear regression analysis. As a predictive analysis, the multiple linear regressions are used to explain the relationship between one continuous dependent variable and two or more independent variables. The independent variables can be continuous or categorical. The estimated form of the model is written as

$$Y = b_o + b_1x_1 + b_2x_2 + b_kx_k + \ldots\ldots (1)$$

where Y - is the value of the response variable, b_o = is the estimate of the intercept while, b_1 b_2 --- bk is the estimate of the slope.

Model of Estimation

The general form of linear regression made with k independent variable in deviation $Y = b_{1x1}b_{2x2}+b_{kxk}$ the normal equation are multiple linear regression model with (3) independent variables of form.

$$Y = \hat{b}_o + \hat{b}_1 x_1 + \hat{b}_2 x_2 \hat{b}_3 x_3 \ldots\ldots (2)$$

$$\hat{y} = \hat{b}_o + \hat{b}_1 x_1 + \hat{b}_2 x_2 \hat{b}_3 x_3 \ldots\ldots (3)$$

Therefore

$$Y = b_1 x_1 + b_2 x_2 + \hat{b}_3 x_3 \ldots\ldots (4)$$

The R-Square Adjusted Criterion

It should be noted that the inclusion of additional explanatory variable in the function can never reduce their coefficient of multiple determination R^2 and will usually raise it. By introducing a new regressor, we increase the value of the numerator of the expression for R^2, why the enumerator remain the same (ey^2, the total variation of y, given in any particular sample). To correct for this defect, we adjusted R^2 by taking into account the degree of freedom, which clearly degrease as new regressor are introduce in the function. The expression for the adjusted coefficient of multiple determination is

$$R^2 = 1 - (1 - R^2)\frac{N-1}{N-K-1} or\ R^2 = 1 - \frac{(\varepsilon\rho^2/n-k-1}{\varepsilon y^2/n-1}$$

Where R^2 is the unadjusted correlation coefficient n in the number of sample observation and k is the using the R^2 criterion with all possible regression approach is to take minimum value (koutsoyiann 1997).

Coefficient of Multiple Regression

When we have (2) two or more independent variable say (k), we take the coefficient of multiple determinations $R^2 y.x_1x_2 \ldots x_k$ it will measure the percentage of total variation in y explained by independent variables $x_1x_2 \ldots x_k$

$$R^2 y = X_1X_2 = \frac{\varepsilon\hat{y}}{\varepsilon y} = 1 - \frac{\varepsilon(\hat{y}-y)^2}{\varepsilon(y-y)^2} = \frac{1-\varepsilon\rho^2}{\varepsilon y^2}$$

To understand this concept, lets partition total variation in an explained and unexplained variation.

Total variation = Explained variation + unexplained variation $\varepsilon y^2 = \varepsilon\hat{y} + \varepsilon\rho^2$

Dividing through by εy^2 we have $\frac{(\varepsilon y)^2}{\varepsilon y^2} = \frac{\varepsilon\hat{y}^2}{\varepsilon y^2} + \frac{\varepsilon\rho^2}{\varepsilon y^2}$

$$1 - R^2 + \frac{\varepsilon\rho^2}{\varepsilon y^2}$$

$$R^2 = 1 - \frac{\varepsilon\rho^2}{\varepsilon y^2}S$$

It can be proved that $R^2 y X_1X_2 \ldots, = X_k \frac{b_1\varepsilon x_1 b_2 \varepsilon x_2 y + \cdots + b_k \varepsilon x_k y}{\varepsilon y^2}$

For model with 3 independent variable

$$R^2 y X_1X_2 \ldots, = X_k \frac{b_1\varepsilon x_1 b_2 \varepsilon x_2 y + \cdots + b_k \varepsilon x_k y}{\varepsilon y^2}$$

Results and Discussion

Table 1: Estimated Regression Coefficients for Possible Regression

Model	Predictor	Coefficients	S. E.	t-value	P-value	Decision
1	Constant	26.154	0.066	399.286	0.000	S
	Humidity	0.000	0.000	-0.842	0.406	NS

Model	Predictor	Coefficients	S. E.	t-value	P-value	Decision
2	Constant	26.762	0.465	57.582	0.000	S
	Rainfall	0.000	0.000	-1.388	0.175	NS
3	Constant	28.435	0.592	48.051	0.000	S
	Precipitation	-0.025	0.006	-3.922	0.000	S
4	Constant	25.701	0.172	149.350	0.000	S
	Wind	0.034	0.013	2.539	0.016	S
5	Constant	26.709	0.491	54.388	0.000	S
	Humidity	0.000	0.000	-0.369	0.709	NS
	Rainfall	0.000	0.000	-1.140	0.263	NS
6	Constant	28.486	0.592	48.150	0.000	S
	Humidity	0.000	0.000	-1.101	0.279	NS
	Prep	-0.025	0.006	-3.958	0.000	S
7	Constant	25.712	0.170	151.412	0.000	S
	Humidity	0.000	0.000	-1.393	0.173	NS
	Wind	0.037	0.013	2.779	0.009	S
8	Constant	28.775	0.666	43.204	0.000	S
	Rainfall	0.000	0.000	-1.097	0.281	NS
	Prep	-0.024	0.006	-3.739	0.001	S
9	Constant	26.282	0.473	55.527	0.000	S
	Rainfall	0.000	0.000	-1.316	0.918	NS
	Wind	0.033	0.013	2.469	0.019	S
10	Constant	27.859	0.629	44.274	0.000	S
	Prep	-0.022	0.006	-3.528	0.001	S
	Wind	0.024	0.012	2.063	0.048	S
11	Constant	28.720	0.675	42.554	0.000	S
	Humidity	0.000	0.000	-0.744	0.463	NS
	Rainfall	0.000	0.000	-0.739	0.466	NS
	Prep	-0.024	0.006	-3.759	0.001	S
12	Constant	27.852	0.615	45.259	0.000	S
	Humidity	0.000	0.000	-1.567	0.128	NS
	Prep	-0.022	0.006	-3.579	0.001	S
	Wind	0.027	0.012	2.350	0.026	S
13	Constant	28.186	0.698	40.362	0.000	S
	Rainfall	0.000	0.000	-1.071	0.293	NS
	Prep	-0.021	0.006	-3.368	0.002	S
	Wind	0.024	0.012	2.025	0.052	NS
14	Constant	27.068	0.625	45.138	0.000	S
	Humidity	0.000	0.000	-0.745	0.415	NS
	Rain	0.000	0.000	-0.728	0.462	NS
	Wind	0.025	0.013	2.057	0.046	S
15	Constant	28.027	0.705	39.781	0.000	S
	Humidity	0.000	0.000	-1.230	0.229	NS
	Rainfall	8.888E-5	0.000	-0.530	0.600	NS
	Prep	-0.021	0.006	-3.435	0.002	S
	Wind	0.027	0.012	2.248	0.032	S

Note: Humidity = X1, Rainfall = X2, Precipitation = X3, Wind = X4

The regression results presented in Table 1 reveal varying levels of influence of the independent variables, Humidity (X_1), Rainfall (X_2), Precipitation (X_3), and Wind (X_4) on temperature. Among the

single predictor models, precipitation (Model 3) and wind (Model 4) were found to be statistically significant predictors of temperature with p-values less than 0.05, while humidity (Model 1) and rainfall (Model 2) were not statistically significant. Specifically, precipitation exhibited a negative coefficient (-0.025), indicating that an increase in precipitation tends to reduce temperature, whereas wind showed a positive coefficient (0.034), suggesting that increased wind speed is associated with rising temperature. This finding aligns with climate variability studies which suggest that precipitation exerts a cooling effect through latent heat exchange, while wind may influence atmospheric heat transfer. In the multiple regression models, precipitation consistently remained significant across Models 6, 8, 10, 11, 12, 13, and 15, while wind was significant in Models 7, 9, 10, 12, 14, and 15. Humidity and rainfall generally remained statistically insignificant across most models, indicating weak explanatory power for temperature variations within the study area.

Table 2: Overall Regression Significance (ANOVA Table)

Model	Source	SS	Df	MS	F-value	P-value	Decision
1	Reg	0.064	1	0.064	0.708	0.406	NS
	Res	2.911	32	0.091	—	—	—
	Tot	2.976	33	—	—	—	—
2	Reg	0.169	1	0.169	1.925	0.175	NS
	Res	2.807	32	0.088	—	—	—
	Tot	2.976	33	—	—	—	—
3	Reg	0.966	1	0.966	15.383	0.000	S
	Res	2.010	32	0.063	—	—	—
	Tot	2.976	33	—	—	—	—
4	Reg	0.499	1	0.499	6.449	0.016	S
	Res	2.477	32	0.077	—	—	—
	Tot	2.976	33	—	—	—	—
5	Reg	0.182	2	0.091	1.008	0.377	NS
	Res	2.794	31	0.090	—	—	—
	Tot	2.976	33	—	—	—	—
6	Reg	1.042	2	0.521	8.349	0.001	S
	Res	1.934	31	0.062	—	—	—
	Tot	2.976	33	—	—	—	—
7	Reg	0.645	2	0.323	4.290	0.023	S
	Res	2.331	31	0.075	—	—	—
	Tot	2.976	33	—	—	—	—
8	Reg	1.041	2	0.521	8.342	0.001	S
	Res	1.934	31	0.062	—	—	—
	Tot	2.976	33	—	—	—	—
9	Reg	0.630	2	0.315	4.164	0.025	S
	Res	2.345	31	0.076	—	—	—
	Tot	2.976	33	—	—	—	—
10	Reg	1.209	2	0.604	10.603	0.000	S
	Res	1.767	31	0.057	—	—	—
	Tot	2.976	33	—	—	—	—
11	Reg	1.076	3	0.359	5.666	0.003	S
	Res	1.899	30	0.063	—	—	—
	Tot	2.976	33	—	—	—	—
12	Reg	1.342	3	0.447	8.219	0.000	S
	Res	1.633	30	0.054	—	—	—
	Tot	2.976	33	—	—	—	—
13	Reg	1.274	3	0.425	7.484	0.001	S
	Res	1.702	30	0.057	—	—	—
	Tot	2.976	33	—	—	—	—

Model	Source	SS	Df	MS	F-value	P-value	Decision
14	Reg	1.342	3	0.358	5.774	0.000	S
	Res	1.634	30	0.062	—	—	—
	Tot	2.976	33	—	—	—	—
15	Reg	1.358	4	0.340	6.087	0.001	S
	Res	1.618	29	0.056	—	—	—
	Tot	2.976	33	—	—	—	—

Note: Reg = Regression, Res = Residual, Tot = Total

The overall regression significance results in table 2 further confirm the reliability of the models. Out of the fifteen estimated models, twelve were statistically significant based on the F-test at the 5% level of significance, indicating that the predictor variables jointly explain substantial variation in temperature. Models 3 and 4 demonstrated that precipitation and wind independently contribute significantly to temperature prediction. However, the strongest overall regression significance was observed in Model 10 (Precipitation and Wind), with an F-value of 10.603 and p-value of 0.000, indicating superior explanatory strength compared to other two-variable combinations. Similarly, Models 12, 13, 14, and 15, which combine three or four predictors, also showed strong overall significance, suggesting that combining climatic variables improves predictive performance. These results are consistent with previous climate studies which established that temperature variability is better explained through the interaction of multiple climatic indicators rather than isolated predictors.

Table 3: Model Evaluation Metrics

Model	Predictors	R^2	Adjusted R^2	MSE	Best Model Rank
1	X1	0.022	-0.009	0.091	15
2	X2	0.057	0.027	0.088	13
3	X3	0.325	0.304	0.063	8
4	X4	0.168	0.142	0.077	12
5	X1X2	0.061	0.000	0.090	14
6	X1X3	0.350	0.308	0.062	6
7	X1X4	0.217	0.166	0.075	10
8	X2X3	0.350	0.308	0.062	6
9	X2X4	0.212	0.161	0.076	11
10	X3X4	0.406	0.368	0.057	5
11	X1X2X3	0.362	0.298	0.063	9
12	X1X2X4	0.452	0.380	0.055	3
13	X1X3X4	0.451	0.396	0.054	**1**
14	X2X3X4	0.428	0.371	0.057	4
15	X1X2X3X4	**0.456**	0.381	0.056	**2**

Table 3 provides further insight into model performance using coefficient of determination (R^2), adjusted R^2, and mean square error (MSE). The results show that Model 10 (X_3X_4), comprising precipitation and wind, recorded a relatively high explanatory power with $R^2 = 0.406$ and adjusted $R^2 = 0.368$, indicating that approximately 40.6% of the variation in temperature is explained by the model. However, Models 12 and 13 demonstrated even stronger performance, with R^2 values of 0.452 and 0.451 respectively, suggesting better predictive accuracy. Model 13 (Humidity, Precipitation, and Wind) recorded the highest adjusted R^2 of 0.396 and the lowest MSE of 0.054, indicating that it provides the best balance between explanatory power and prediction error. This suggests that the combined effect of humidity, precipitation, and wind offers the most robust model for predicting temperature in this study. The findings imply that precipitation and wind are the dominant climatic factors influencing

temperature, while humidity contributes meaningfully only when combined with other significant predictors. These results are in line with the study's objective of identifying the most appropriate regression model for explaining temperature variability and support existing empirical evidence that temperature is influenced by complex interactions among climatic variables.

Conclusion

This study successfully modeled the relationship between temperature and selected climatic variables using possible regression analysis. The findings established that precipitation and wind are the most significant determinants of temperature variation, while humidity and rainfall contributed minimally when considered independently. The overall regression results confirmed that most of the estimated models were statistically significant, indicating that climatic variables jointly explain temperature fluctuations.

Among all the estimated models, the combination of humidity, precipitation, and wind emerged as the most suitable model due to its superior explanatory power and lowest prediction error. This demonstrates that temperature variation is best explained through the combined influence of multiple climatic factors. The study therefore concludes that multiple regression modeling is an effective statistical approach for predicting temperature and understanding climate dynamics. These findings can support environmental planning, climate forecasting, and policy formulation for sustainable climate adaptation and mitigation strategies.

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